REVIEW ARTICLE

Solar Power Forecasting Methods – A Review

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ABSTRACT: Solar power forecasting is crucial for the purpose of ensuring grid stability and proper grid management. Recent advancements with inside the discipline of solar power forecasting are presented, and the main focus is on the different types of Machine Learning (ML) Techniques used. These ML techniques can solve both the complex and nonlinear data structures. The two types of solar power forecasting are direct and indirect. It entails three models namely: plane of array irradiance, estimating solar irradiance forecast, solar performance. For the purpose of classification of solar power forecasting we take into consideration 3 main parameters such as the Forecast Horizon, Input Parameters and the Forecasting methodology. During the failure of the real-time data acquisition or with inside the case of unavailability of solar power for a new PV plant the concept of Indirect solar power forecasting can be used. According to recent studies models like the hybrid models, deep neural networks take over the conventional methods of the short-term solar forecasting. Data-preparation techniques and various intelligent optimizations enhance the performance accuracy.

KEYWORDS: Optimization, Direct Forecasting, Indirect Forecasting, SVM, ELM, ANN, MLR, Forecast Horizon, Global Horizontal Irradiance.

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INTRODUCTION

Due to rapid exhaustion of the fossil fuels and the concept of the Global warming the non renewable energy sources have been losing importance. To estimate the performance of PV installations in the approaching years the effect of global warming have been analyzed by Peters et al.,[1]. In case of the Industrial and home loads solar energy is of primary importance [2] but only demerit is that they are unpredictable in nature. Different amounts of electricity are generated by solar plants in case of various climatic condition and solar radiation [3]. There has been more change noticed in case of the output power. This change can happen at any time and it is not constrained [4]. This often leads to load-generation incongruity in the grid, thus on the whole making the solar power forecasting quite vital, more important while taking into consideration of the high penetration solar grid [5].

The Grid integration with the renewable energy sources is quite complex. The Grid management complexity occurs due to the fitful perspective of the solar energy and moreover balancing the electrical energy generation and consumptions becomes challenging [6]. Most common issues that arise during the generations and consumption are voltage fluctuations, low power quality, instability. Asynchronous operations, variability and uncertainty are the main technical challenges that the operators are supposed to deal with while integrating renewable energy with the grid [7]. For the purpose of optimal management of the electrical grid accurate forecasting of solar power is essential [8]. In case of dealing with the generated power, scheduling, minimizing the cost of production of electrical energy, overcrowding management and for the purpose of better operation of the power grid. Solar power forecasting is required. While the penetration of the grid increases the solar power prediction is critical. For the purpose of controlling electricity variation usage of storage systems with renewable energy is suggested by many researches.

For the purpose of maintaining a continuous flow of electricity, to dampen the fluctuations and to absorb excess power mostly the storage systems are being preferred. Forecasting

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Techniques of PV power are: (i) direct forecasting that uses the historical data of PV power to predict the power directly and (ii) indirect forecasting, that makes use of climatic variables and the solar irradiation forecasting that directly affects solar power production [9]. Among the numerous models presented the most commonly used physical model for the concept of Forecasting is the Numerical Weather Prediction (NWP). The Atmospheric variability and its unpredictable nature have made the numerical weather prediction model much more intense and quite complicated in case of the calculations [10]. The Machine learning technique has become popular due to its ability to deal with non-linearity. Collation of the diverse Solar PV performance model, estimation models in the field of PV power forecasting is presented. This review paper aims on identifying the most effective forecasting methodologies available in case of both the direct and indirect based on certain input parameters.

Energy Management and Auditing

Energy Management is a proactive approach for the purpose of conversion, distribution, and utilization of energy in order to meet the requirements, taking into account environmental and economic objectives. The primary objective of energy management is to maximize profit and minimize costs. It includes conserving energy, thereby reducing the cost and cultivating good communications on energy matters. Moreover it aids in developing and maintaining effective monitoring, reporting, and management strategies for efficient energy usage.

Energy management can be broken down into a number of key areas namely: Preparing for the formulation of the Policy Statement, Appointing the Energy Manager, Planning, Monitoring and control, Conduction of an Energy Audit, Motivation of People. Electricity is generated at power stations, and then bought by suppliers, who then sell it on to meet the needs of the consumers. Electricity trading refers to the transaction between power generators, who produce electricity, and power suppliers, who sell it on to consumers.

Energy trading is conducted by asset-trading companies that use production, demand, and price forecasting to optimize the revenue created from energy production. Apart from production forecasts, energy traders analyze pricing and the demand trends in order to determine the ideal strategy for keeping in trend with the energy market. In addition to that the energy traders take them fully responsible for the produced energy and inherit any risks associated with trading an asset on the market. Risks include revenue losses via under- and over commitment of projected production.

Energy Scenario in India

India's energy sector is one of the most vital sources that make an impact on the India's economic growth and welfare. The three main categories of energy are: Primary and Secondary energy; Commercial and Non-commercial energy; Renewable and Non-Renewable energy. Tackling the climate change poses a huge threat due to increase in demand. Total final energy consumption decarbonizes as fossil fuels are being replaced by electricity and hydrogen. The share of fossil fuels in primary energy declines as there exists a hike in the renewable energy. Similarly trend towards a lower carbon fuel mix is present in the case of primary energy, as there exists a decline in the usage of fossil fuels moreover there is a rapid growth in the usage of renewable energy. The renewable energy, share in primary energy accounts to an increase of over 10% in 2019 and estimated to increase around 55-65% by 2050. The speed of the change in energy depends upon the natural gas demand. There exists an increase in the usage of Solar and wind. There exists a rise in the Electricity demand as the world has started to increasingly electrify. The total primary energy consumption of fuel has reached a new momentum 760 p.a.

PV Power Forecasting Methodologies

The two types of solar power forecasting are (1) Direct forecasting, can be used to directly forecast the PV power (2) Indirect forecasting, are also based on the solar radiation forecasting for forecasting PV power indirectly. Short-term forecasting is a quite challenging task for many of the people who are into research field. PV power forecasting is a non-linear problem, which depends upon several weather parameters. Finding the proper parameter estimation method is a difficult task for a non-linear system. Two major categories of models are (i) physical models and (ii) data-driven models. Choice of the model depends upon forecast horizon and the location.

Numerical Weather Prediction model is used mostly in common. It makes use of the dynamic atmosphere model and mathematical equations for N-step ahead forecast horizon radiation prediction. Data driven models are also the other type of the forecasting. This model according to [32] predicts the output based on the extraction of useful information from the input training data. The quality of the training data predicts the performance of these methods. Machine learning based models shows better performance for short-term forecast horizons.

Optimization Techniques

The particle swarm optimization which is termed as (PSO) is a technique that is mostly used to optimize a problem with regard to quality by means of improving the candidate solution iteratively.PSO is comparatively a simple concept to implement, and computationally more efficient when compared with the algorithms and the heuristic optimization techniques. PSO has more benefits compared to GA. They are easily programmable and mostly provide a better solution.

A genetic algorithm (GA) is being widely used to solve the optimization problems. This algorithm is considered to be the subset of evolutionary algorithms. Genetic algorithms can be used to implement the concept of genetics and natural selection for the purpose of providing answer to the encountered query [33].

The Whale Optimization Algorithm (WOA) can be made to use in order to solve optimization problems [34]. Three operators are considered here for the purpose of simulating the search for prey, encircling the prey, and bubble-net foraging behaviour of humpback whales.

Extreme learning machine (ELM) is considered to be a training algorithm used for the purpose of solving the single hidden layer feed forward neural network (SLFN according to [35] which is considered to converge much faster than the fore-mentioned traditional methods and the performance is also quite promising.

Support Vector Machine (SVM) algorithm is mainly preferred for the concept of classification and regression [36]. The objective involved in the SVM algorithm is the need to identify the hyperplane in an N-dimensional space that can be used to distinctly classify the data points. It can be used to handle both classification and regression in case of linear and non-linear data.

Artificial neural network (ANN) can be used for the purpose of processing the elements that can receive inputs and can deliver the outputs based on certain predefined activation functions. It can also be used to develop certain algorithms for modelling the complex patterns and prediction problems [37].

Direct Forecasting

Online 24-h Solar Power Forecasting Based on Weather Type Classification Using Artificial Neural Network was reported by [10]. It was found that the performance of the neural network is improved by means of the weather classification factor according to which was carried out in China with the Forecast horizon of 1-d for a period of 1 year having the input variables like Solar Power, weather forecasted data (wind speed, solar irradiance, air temp, cloud, pressure of the air, sunshine hours, air pressure, and the presence of humid) using the methodology Radial Basis Function Network, Self Organizing Map, K-fold cross-validation. From the proposed model it was validated that the error obtained is less than 5% for 1-d ahead horizon and it can be extended for a broader forecast horizon according to [11], which was carried out in Italy with the Forecast horizon of 1-d for a period of 1 year having the input variables namely time and Solar irradiance as exogenous, and the PV power as endogenous Feed Forward Neural Network.

It was validated that from all the forecast horizons the proposed model outperformed the single-stage models (DE and PSO) [12] which was carried out in Australia with the Forecast horizon of 1h, 2h, and 4h for a period of 2100 hourly samples for training input variables Air temperature, PV power, relative humidity solar irradiance using the methodology differential evolution and PSO. On comparison to the single-stage models ensemble model it was found that assigned model performed better while training and forecasting stage, which was carried out in Australia with the Forecast horizon of 1-d for a period of 5 years having the input variables weather temperature, PV power, Speed of the wind, and its direction using the methodology

DHI Ensemble of support vector machine global horizontal irradiance, humidity, mars. On validation it was established that the aggregation of the solar sites has improved the output by minimizing the effect of variability and added to this it has also been found that the GB and random forest outweigh both individually and aggregation of 152 PV sites according to Liu et al., [13] which was carried out in the Netherland with the Forecast horizon of 1-d for a period of 3 years having the input variables weather condition variables like (pressure, temperature, cloud cover, wind vectors, clear sky radiation precipitation), PV power generation using the methodology l-support vector machine, k support vector machine, GB, random forest, feed forward neural network, LASSO, MLR.

It has been initiated that the over-fitting issues are mitigated by the proposed model by means of smoothing input data series [14] and the experiment was done in Taiwan with the Forecast horizon of 1-d for a period of 1 year having the input variable PV power using the methodology GT-DBN which is termed as the grey theory based deep belief neural network in the data series. On construction of the new model it was validated that the RNN, Multilayer Perceptron, LSTM and GRU are outperformed by the given model [15] which was carried out in China with the Forecast horizon of 1-h for a period of 2 years having the input variables global horizontal irradiance, Solar power, DHI, temperature, humidity, wind speed using the methodology WPD-LSTM.

It was validated that the PSO has been used for the purpose of optimization of the parameters of LSTM. The proposed model performs better than the LSTM, artificial neural network, and extreme gradient boosting [14], reported in China with the Forecast horizon of 30-min for a period of 1 year having the input variables PV power, sunshine, temperature, wind speed, humidity using the methodology PSO-LSTM. On integrating a selective layer with the automatic input selection hidden layer a model was proposed and it delivers superior performance [17] was studied in Morocco with the Forecast horizon of 1-h for a period of 2 years having the input variables temperature, Solar energy, DHI, humidity, rainfall, wind speed and direction, global horizontal irradiance using the methodology DNN-RODDPSO.

For the purpose of choosing an appropriate models among the various quite familiar models and methodology was proposed based on median, regression, mean which was termed as the combined forecast methodology [18]. This was carried out in INDIA with the Forecast horizon of 1-d for a period of 2 years having the input variables as that of the numerical weather prediction-derived variables like cloud cover, humidity, pressure, PV irradiance, precipitation using the methodology ensemble trees, Gaussian Process Regression, Persistence, Linear regression, Feed Forward Neural Network, LSTM, SVR. On construction it was found that the Support Vector Machine, Back propagation Neural Network, seizure detection algorithms, Support Vector Machine , persistence, SDA ELM are taken over by the proposed model models for the same dataset which was carried out in China with the Forecast horizon of 1-d for a period January 2017- October 2018 having the input variables Max, min and ambient temperature, Global Horizontal Irradiation/Irradiance, and Diffused Horizontal Irradiance using the methodology Similar day analysis, Genetic algorithm, Extreme learning machine. Validation has been carried out on the system and using the results it was found that that the similar day analysis extreme learning machine, extreme learning machine, support vector machine , BPNN, persistence models with the same data was outweighed by the proposed models for the same dataset [20] was carried out in China with the Forecast horizon of 5 min having the input variables Solar power, speed of the wind, intensity of the radiation, temperature using the methodology ICSO in Extreme learning machine.

Indirect Forecasting

It was reported that the copula model was outperformed by the Markov-chain mixture (MCM) model and the results obtained were matching with quantile regression probabilistic model [21], which was validated in Sweden with Forecast horizon of 1-d for a period of 1 year having the input variables Global Horizontal Irradiance, clear sky irradiance using the methodology MCM distribution and copula model. Validation has been carried out on the category of better performance and very minimum error in the forecast a model was designed to overcome the other designs depicted [22] in Australia with the Forecast horizon of 1 month for a period of 1905–2018 having the input variables maximum

Temperature, minimum Temperature, Rain, pressure of the vapor, relative humidity on both the ranges maximum and minimum, using the methodology MEMD Ant colony optimization RF. While taking into consideration the minimum centered Root Mean Square Error and Root Mean Square Error the results were found to outweigh the research of the weather and forecasting model [23] was carried out in USA with the Forecast horizon of 24-hour for a period of May to September 2014–2017 having the input variables Condensation level of lifting, Strength of inversion, tropospheric total water mixing ratio, Potential water temperature, surface temperature of the dew point.

It was validated in China that the identified two models accurately forecast the Global Horizontal Irradiance in the humid region [24] with the Forecast horizon of 1-d for a period of 2001–2015 having the input variables global horizontal irradiance, sunshine duration, humidity, max and min temperature, and precipitation using the methodology KNEA and Cat Boost. The model proposed was based on the different climatic condition under which the model is successful, validated that the heuristic algorithms and Support vector machines -BAT increased the Aaccuracy of the performance followed by Support vector machines -PSO and Support vector machines -WOA [25] reported in China with the Forecast horizon of 1-d for a period of 3 years having the input variables global horizontal irradiance, diffuse solar irradiance, sunshine duration, max and min temp, PM2.5, PM10 and O3 using the methodology. Support vector machines -PSO, Support vector machines -BAT and Support vector machines –WOA. By making use of the particle swarm optimization it was found that forecasting accuracy enhances by means of parameters for the purpose of optimization using the Extreme Learning Machines [26]. This study was reported in China with the Forecast horizon of 1-d for a period of 1961–2016 having the input variables Solar irradiance, sunshine hours, relative humidity, average, maximum and minimum temp of the air using the methodology particle swarm Optimization, Extreme learning machine.

For the purpose of minimizing the dimensions, the feature dimension MEMD-Singular value decomposition based model was presented by Prasad et al., [27] in Australia with the Forecast horizon of 1-week for a period of 1905–2018 having the input variables FAO56, Vapor pressure, evaporation, relative humidity at maximum and minimum temperature, rainfall, maximum and minimum temperature using the methodology of MEMD-singular value decomposition- random forest. Due to the scarcity in the ground based data source the Satellite-based measurements was preferred for the purpose of solar resource forecasting [28]. This study was carried out in Singapore with the Forecast horizon of 1-h for a period of 3 years having the input variables Ground and satellite-based solar Irradiance using the methodology Cubist, SVR, GLMNET, Random Forest, PPR. Comparing the ML models the depicted model reduced the forecasting error by 40% [29] reported in India with the Forecast horizon of 1-h for a period of 10 years having the input variables Global horizontal irradiance, relative humidity, temperature, speed of the wind and its direction, pressure, clear sky index using the methodology Extreme gradient boosting- Deep neural network.

The Artificial Neural Network models outweighed the models such as the emp Xirical models [30] was used in India with the Forecast horizon of 1-d for a period of 3 years having the input variables Max-min temperature, DT, approximate sunshine hours(So), Terrestrial radiation(Ho), Theoretical sunshine hours(Sa) by making use of the methodology Artificial Neural Network. It was found that the cubist models performed well for large datasets, and bag Earth generalized cross-validation found independent with a dataset [31]. This work was carried out in India with the Forecast horizon of 1 h-48 h for a period of 5 years solar radiation using the methodology FoBa, Leap Forward, spike slab, Cubist, bag Earth Generalized Cross-Validation. By making use of the ANN we can learn and also able to model the complex and non-linear relationships, which is found to be quite vital. This is because in the real-life, more of the equations and relations between the inputs and the outputs are found to be non-linear and also found to be complex.

The ANN model [37] can also be termed as the "black box" model which can be used for the purpose of modelling the non linear dataset as well as the high dimensional dataset. But mostly we make use of ANN to solve the problems such as the prediction problems in case of certain system. ANN model is almost similar to that of the nerve cells in case of the human brain.

CONCLUSION

A detailed review of the Direct and Indirect methods of forecasting systems was reported. The solar power output is forecasted directly in case of Direct Forecasting, while in case of Indirect Forecasting the prediction is indirect. The list of indirect PV power forecasting is: PV radiation forecasting, plane of array MEMD-ACO-RF, Ant colony optimization, low centred Root Mean Square Error, Particle swarm optimization, Whale Optimization Algorithm, Support vector machines particle swarm Optimisation, Extreme learning machine particle swarm Optimisation, Extreme Learning Machines, Singular value decomposition Random Forest Artificial Neural Network estimation and PV performance models. While in the case of Indirect forecasting techniques indirectly solar power is forecasted. Analysis was carried out on the concept of solar power forecasting methods; the list of techniques used; forecast horizon and input parameters have been presented. The following points were noted: firstly, an indirect solar power forecasting is used, when direct solar power forecasting is not classified using the given Machine Learning techniques. For instance, the case of freshly-started Solar plant and secondly Most of the Ensemble methods are used when compared to other models depicted for forecasting.

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